UNITED STATES DISTRICT COURT
EASTERN DISTRICT OF NEW YORK

BARBARA SCHWAB et al., individually and on behalf of all others similarly situated, Plaintiffs, v. PHILIP MORRIS USA, INC. et al., Defendants.	Case No. CV-04-1945 (JBW) (SMG)

Expert Witness Report by:

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I. Introduction and Qualifications

1. My name is Dr. John R. Hauser. I am the Kirin Professor of Marketing at the MIT Sloan School of Management at the Massachusetts Institute of Technology ("MIT"). I have served MIT in a number of capacities including Head of the Marketing Group, Director of the Center for Innovation in Product Development, and Director of the International Center for Research on the Management of Technology. I have recently been appointed Area Head for Management Science at MIT. The Management Science Area at the MIT Sloan School of Management includes the Marketing Group, the Statistics Group, and other groups. The principal focus of my research and teaching at MIT has been in the areas of marketing management, new product and service development, consumer satisfaction, marketing research, and competitive marketing strategy.

2. I am the author of over sixty articles and papers, as well as the textbooks *Design and Marketing of New Products* and *Essentials of New Product Management*. In addition, I served as editor-in-chief of *Marketing Science* and have held senior editorial positions with *Management Science* and the *Journal of Product Innovation Management*. I have also received numerous awards for excellence in research and teaching in marketing and marketing research, and was recognized by the American Marketing Association with the Converse Award for "outstanding contributions to the development of the science of marketing." In September of 2001 I received the Parlin Award, "the oldest and most distinguished award in the marketing research field," according to the American Marketing Association.[1] I am a trustee of the Marketing Science Institute.

3. I have served as an expert witness in connection with a range of disputes. Most of this

[1] See www.marketingpower.com and type in Parlin Award in search box. Click the link that says "Parlin Award." The direct link is http://www.marketingpower.com/live/content.php?Item_ID=1097. Visited July 7, 2005.

expert testimony has involved surveys and other market research to measure consumers' attitudes, beliefs, and intentions. I have been called upon to project what consumers would have done in different market scenarios, to measure the importance of product features, to measure the impact of rumors, to evaluate marketing research with respect to advertising claims, and to investigate the potential for consumer confusion. I have also consulted to dozens of major corporations, including General Motors, Fidelity Investments, American Airlines, Procter & Gamble, and IBM. My professional qualifications are described in my curriculum vita, which is attached as Exhibit A. A list of cases in which I have testified within the last four years at deposition or trial is attached as Exhibit B.

II. Assignment

4. I was asked by counsel for Plaintiffs, to assess the value and importance of health risks to "light" cigarette consumers in their decision to purchase a "light" cigarette.[2]
5. In undertaking this assignment, I relied on my extensive expertise in developing, testing, and analyzing surveys and in interpreting qualitative and quantitative research about consumer attitudes, intentions, and behavior.
6. My work is ongoing; I may update and revise my results and conclusions as I review additional data and information. A complete list of materials I have considered to date in connection with this particular assignment is included as Exhibit C. To the extent that I

[2] In response to a ruling by the court on the issue of statute of limitations, counsel for Plaintiffs also asked me to conduct a test survey to determine whether accurate dates could be obtained from respondents regarding when they first learned that light cigarettes are no less harmful than regular cigarettes, and when they first learned that the cigarette companies had defrauded them. After attempting to conduct such a survey, I have concluded that I would have little confidence that the responses would be sufficiently accurate. I do not rely on any such survey as part of my expert opinions in this case.

review additional information, I will supplement this list.

7. Part of the work for this investigation was performed under my direction by others at Applied Marketing Science, Inc. ("AMS"). I am a Senior Consultant for and Co-Founder of AMS.

8. My rate of compensation for this task is $650 per hour. My compensation is not contingent upon the outcome of this dispute.

III. Summary of Conclusions

9. The scientific methodology used to design, execute, and analyze the study in this report is sound, reliable, and valid. The results can be relied upon to draw inferences about whether health risks are a significant contributing factor in consumer decisions to smoke "light" cigarettes and what proportion of "light" cigarette-smoking consumers relied on health risks as a significant contributing factor. The results can further be relied upon to draw inferences about how consumers and the market would react to cigarettes would different levels of health risks.

10. Based on the methodologies described in this report and based on calculations of the importance of health risks as a factor in consumer decisions, consumer willingness to pay for lower health risk, and market-based simulations, I conclude that health risks are a positive contributing factor in the choice of "light" cigarettes for 90.1 percent of "light" cigarette consumers and, of these consumers, on average, it is ranked above all other measured features, excluding price, (i.e., taste or packaging). It is ranked above at least one other feature by 97.8 percent of the consumers, indicating its significance for the overwhelming

majority of respondents.[3]

11. The methodologies described in this report provide data with which to calculate the market value of the change in perceived health risks for "light" cigarettes. In this report I provide two examples of how one might calculate the market value. These examples suggest that the market value of a decrease in health risks from the same as regular cigarettes to the same as "light" cigarettes is between 39.8 percent and 47.3 percent of the price per pack.

12. For "light" cigarette consumers, the data and analyses in this report can be used to simulate "but for" scenarios in which "light" cigarettes with varying health risks are available on the market. For example, if each brand of "light" cigarettes offered two versions of "light" cigarettes, one version with the perceived health risks the same as "light" cigarettes at regular price and another version with the perceived health risks the same as regular cigarettes but at a 50% reduction in price, then the "light" cigarettes with the better perceived health risks would obtain a market share between 46 and 48 percent.[4]

13. The data and analyses in this report can be used to gain insight on the price discount that would be needed to sell a cigarette with perceived health risks <u>greater</u> than regular cigarettes. For example, more than 75 percent of the consumers would be willing to pay more than 50 percent of the price per pack to decrease health risks from greater than regular cigarettes to health risks the same as "light" cigarettes. One estimate of the market value of a perceived decrease in health risks from greater than that of regular cigarettes to that the same as "light" cigarettes is substantially more than 50 percent of the price per pack.[5]

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[3] Health risks are ranked above price by 26.8 percent of these consumers, above taste by 68.9 percent of the consumers, and above pack type by 94.4 percent of the consumers. Health risks are ranked above price or taste by 76.1 percent of these consumers.

[4] The estimates are 47.7 percent for a market simulation based on first choices and 46.1 percent for a market simulation based on randomized first choices.

[5] The largest price discount examined in the survey was a 50% percent discount, hence, conservatively, I do not simulate any market with a price in which a brand uses a discount of more than 50%. If each brand of "light"

14. At most 8/10ths of 1 percent of the respondents use a non-compensatory lexicographic decision rule for taste, health risks, pack type, and price. For all other respondents and for the features of taste, health risks, and price, high levels on some features can compensate for low levels on other features.

IV. Overview of Methodology

15. The basic methodology that I selected is known as web-based conjoint analysis. Conjoint analysis is a tool that enjoys wide use in the field of marketing research. It was introduced to the field of marketing research in 1971 and is generally recognized by marketing science academics and industry practitioners to be the most widely studied and applied form of quantitative consumer preference measurement. It has been shown to provide valid and reliable measures of consumer preferences, and these preferences have been shown to provide valid and reliable forecasts of what consumers will do (or would have done) under scenarios related to those measured.[6] For example, under the auspices of MIT's Virtual Consumer Initiative, my colleagues and I have undertaken large-scale tests of the validity of web-based conjoint analysis. Predictions were highly accurate. One of the scientific papers discussing the validity test recently received two highly prestigious awards as the best paper in the marketing sciences literature for 2003 (awarded in 2004) and for the best paper based

cigarettes offered two versions of "light" cigarettes, one version with perceived health risks the same as "light" cigarettes at regular price and another version with perceived health risks greater than regular cigarettes but at a 50% reduction in price, then the "light" cigarette with better perceived health risks would obtain a market share between 72 and 76 percent. The estimates are 75.4 percent for a market simulation based on first choices and 72.3 percent for a market simulation based on randomized first choices. Details are provided later in this report.

[6] Hauser, John R. and Vithala Rao (2004), "Conjoint Analysis, Related Modeling, and Applications," *Advances in Marketing Research: Progress and Prospects*, Jerry Wind and Paul Green, Eds., (Boston, MA: Kluwer Academic Publishers).

on a dissertation (awarded in June 2005).[7] Another scientific paper was a finalist for the best paper in 2002 in the *Journal of Product Innovation Management* and still a third paper was a finalist for the best contribution to the practice of marketing research in 2004.[8]

16. The general idea behind conjoint analysis is that consumers' preferences for a particular product are driven by features or descriptions of features embodied in that product. For example, a cigarette might be described by features such as: (i) pack type (hard or soft); (ii) degree of perceived health risks; (iii) taste; and (iv) price. A feature, such as perceived health risks can have many levels such as less than "ultra-light" cigarettes, the same as "ultra-light" cigarettes, the same as "light" cigarettes, the same as regular cigarettes, and greater than regular cigarettes. (Detailed wording and descriptions of these levels are provided later in this report.) When applying (decompositional) conjoint analysis respondents are asked to make holistic judgments about products (or product descriptions) or to choose among products (or product descriptions). That is, consumers are shown product profiles made up of the features or descriptions of features and asked to indicate their preferences for these profiles or to choose among these profiles ("choice task"). The conjoint analysis methods use the holistic judgments or choice tasks to decompose respondent preferences for a product into the partial contribution of these feature levels or descriptions ("partworths"). These partworths are then estimated from respondent preferences or choices with the appropriate statistical methods. The partworths for feature levels are identified with the estimation methods so that the partworths best predict consumer preferences or choices. The difference between the smallest and largest partworths for levels of each feature can be used to calculate the relative

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[7] Toubia, Olivier, Duncan I. Simester, John R. Hauser, and Ely Dahan (2003), "Fast Polyhedral Adaptive Conjoint Estimation," *Marketing Science*, 22, 3, (Summer), 273-303.

[8] Dahan, Ely and John R. Hauser (2002), "The Virtual Consumer," *Journal of Product Innovation Management*, 19, 5, (September), 332-354;Toubia, Olivier, John R. Hauser, and Duncan Simester (2004), "Polyhedral Methods for Adaptive Choice-based Conjoint Analysis," *Journal of Marketing Research*, 41, 1, (February), 116-131.

importance of each feature in purchase decisions. Importance refers to the relative value of changing that feature from its least preferred level to its most preferred level. The partworths for changes in price levels measure the relative importance of changing price. The price reduction needed to compensate for a lower (less-preferred) level of a feature, or the additional price consumers would pay for the higher (more-preferred) level of feature can then be calculated.

17. There are many forms of conjoint analysis, most of which provide valid and reliable data. For this assignment, I selected a form of conjoint analysis known as Choice-Based Conjoint ("CBC") analysis. In CBC, consumers are shown sets of profiles (called the "choice sets"), and asked simply to choose the profile that they most prefer, that is, the profile that they would choose if the choice set described the only products that were available. I chose to show respondents four products in each choice set. I have used four-product choice sets in other applications and have found the data to be both reliable and valid.

18. Choice-Based Conjoint analysis is consistent with economic theories of approximate utility maximization. That is, if a researcher could measure each and every feature of the product and represent consumer utility as a function of those features, then consumers would choose the product that maximizes their utility. This utility is composed of the features that are measured (as represented by the partworths) and features that are not measured (random component). To estimate the partworths, I use a statistical method known as Hierarchical Bayes ("HB"). HB is based on "Bayesian" methods. In lay terms, a Bayesian method uses the data, that is, the respondent's choices in the questionnaires, to update any prior beliefs, such that the resulting partworth estimates make the best use of the data. The "hierarchy" part of HB means that the estimates for a given respondent are based on the choices by that

respondent and informed by the choices of other respondents. This information is used iteratively, so that the resulting partworth estimates most accurately reflect all of the data in the sample. HB has proven to provide reliable and valid conjoint analysis estimates of partworths. It is an appropriate method to use to obtain partworths when there are a moderate number of choice sets in the choice task. This enables me to appropriately balance the number of questions in the choice task with the number of partworths that need to be estimated. I have observed in other conjoint surveys that I have conducted that such designs limit respondent wear-out.[9]

19. The form of partworth estimation that I selected allows consumer preferences to be heterogeneous. That is, each respondent in the sample can have different values for his or her partworths. For example, one respondent might prefer the taste of regular cigarettes and another might prefer the taste of "light" cigarettes. One respondent might value having a lower health risks highly and another less highly. In technical terms, I estimate a separate "vector" of partworths for every respondent.[10]

20. Based on the measured features and random component, I predict the probability that a respondent will choose any product profile that is described by the partworths and can do so for any competitive set of products described by the measured features. The probability-of-choice calculations are based on an "extreme-value" distribution, and the analysis method is commonly referred to as the multinomial logit model. This is the appropriate distribution to use in this context because, in making their selections, consumers are maximizing their utility. When price is one of the measured features, the value consumers place on each of the

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[9] If too many questions were asked of a respondent, then the respondent might "wear out," that is, response errors might increase as the respondent tires. Not only did I limit the number of questions in the choice task to minimize wear out, but I pretested the questionnaire to assure that respondents did not experience wear out.

[10] Technically, we also have a full characterization of the (posterior) distribution of partworths for each respondent. This full characterization is used in the randomized first choice method described later in this report.

other features can be expressed in terms of price. That is, the price reduction needed to compensate for having a lower level of a feature, or the additional price consumers would pay for having a higher level of a feature can be calculated. I also simulate how choice shares would change in a market based on a change in overall price.

21. Because CBC is based directly on consumer choices, it is, in my opinion, an ideal method to determine the value that consumers place on the various features of cigarettes. In particular, CBC can determine the value that consumers place on having reduced health risks as part of their "light" cigarette. CBC can also assess the significance of health risks as a contributing factor in consumers' decisions to smoke "light" cigarettes.

V. Questionnaire Development

22. I began by identifying the features that drive "light" cigarette consumers' purchases of cigarettes. I instructed AMS to conduct in-depth interviews with current "light" cigarette consumers. A total of 14 interviews were conducted on March 9th, 2005. From these interviews, both AMS and I learned more about the features of cigarettes and how these features affect consumers' purchasing decisions. These interviews enabled me to identify the appropriate features to use in the web-based, Choice-Based Conjoint analysis and to develop a questionnaire that used words and phrases that consumers use to describe the features of cigarettes. These interviews assured that the words used to describe the levels of the features were understood by consumers. This questionnaire was programmed into a web-based software system designed for administering and analyzing such questionnaires.[11] Examples of the final questionnaires that respondents were asked to complete are shown in Exhibit D.

[11] I used Sawtooth Software, Inc.'s SSI Web Version 3.5.0 package, which is a well-known and widely used software system for these types of applications.

Recall that respondents answered these questions via their computers. Exhibit D contains reproductions of the computer screens. In addition, some questions, such as the choice task, were chosen based on algorithms that included appropriate randomization to avoid order effects. Thus, Exhibit D is an example of the types of screens that respondents viewed.

VI. Pre-testing the Questionnaires

23. The questionnaires were pre-tested with 9 respondents on March 25th through March 29th, 2005 to ensure that respondents understood the descriptions, instructions, and questions and that their answers adequately represented their beliefs. Minor changes in the wording and formatting of the questions were made as a result of the pretest to assure that respondents understood the questions and that the interview flowed smoothly. Respondents were debriefed to ensure that the questionnaire maintained a "double-blind" protocol. In a double-blind protocol, neither the interviewer nor the respondent is given either explicit or implicit cues from which to guess the purpose of the study. In this case, the "interviewer" is the web-based questionnaire, so we need debrief only the respondents. Following standard procedures, no pretest responses were included in the final sample.

VII. Identifying the Sample

24. For this survey, potential respondents were selected at random from Greenfield Online's database and sent an invitation (Exhibit E) to go to a special website to complete the survey. Each invitation included a URL with an embedded password that was then matched against a list of valid passwords and against the list of passwords that had already been used. (The former assures that only valid respondents complete the questionnaire. The latter assures that

each respondent completes the questionnaire at most once.) Respondents received an initial e-mail invitation and up to four e-mail reminders. Greenfield Online motivates respondents to participate in these surveys by adding $5 to the Greenfield prize accounts of all who qualify for and complete the survey. In my experience, such incentives increase response rates but do not bias any of the responses to the questions in the survey.

25. In order to qualify for the survey, respondents were screened to assure that they were "light" cigarette consumers. A total of 627 respondents completed the survey beginning on June 15th, 2005 and ending on June 29th, 2005. The completion rate was 94.9 percent. Details are provided in Exhibit F.

26. To assure a nationally representative sample of respondents, quotas were set so that the sample would match the national data on Census region, sex, age, and household income. These respondents were allocated to the seventy-two quota groups (four Census Regions crossed with two levels of sex, three levels of age, and three levels of household income, 72 = 4x2x3x3).[12] Based on information from Greenfield Online, I estimated that 12.5% of the respondents would be "light" cigarette consumers. In order to identify approximately 500 "light" cigarette consumers to interview, the study would need to identify approximately 4,000 respondents allocated proportionally to the quota groups. In order to identify these 4,000 potential respondents, 7,738 potential respondents were screened. Exhibit F shows the number of respondents in each group and the number completing the conjoint task. The completed interviews match closely the screening quota and the census categories.[13]

27. In my experience one obtains the same partworth estimates (up to normal sampling variation)

[12] Because the respondents are smokers, the respondents must be 18 years of age to participate.

[13] There is no reason to expect that the penetration of "light" cigarette consumers will match the distribution of census regions and/or the distribution of age, sex and household income. The screening assures we start out with a representative sample. The final sample reflects the distribution of "light" cigarette consumers as observed.

from web-based and from central facility respondents. For this assignment, I followed protocols designed to maximize the response rates to the surveys.[14] It is my opinion that these protocols are sufficient to assure that the respondents are representative of the sampled population.

VIII. Survey Administration

28. After the initial screening for representativeness, respondents were asked whether they smoke cigarettes and, if so, which type they primarily smoke. Only respondents who were "light" cigarette consumers were asked to continue the interview.

29. Respondents were asked how long they had been smoking, what type of cigarette they had smoked primarily when they began smoking, and how long ago they began to smoke primarily "light" cigarettes. They were asked how many packs per day they smoke and asked to indicate which brand of "light" cigarette is their primary brand. Respondents were then introduced to the conjoint task and shown a list of the features that would be varied in the product profiles that were to follow.

30. Respondents were then shown a series of sixteen screens (choice sets) containing four alternative cigarette options that were described by the combinations of the features that had been identified by qualitative research. For each set of four alternative cigarette options, respondents were asked: "If these were your only options, which would you choose?" Prior to the choice exercise, respondents were instructed to choose from each choice set the cigarette option they would choose as their primary cigarette option. Respondents indicated which of the four cigarette options they would choose. The features and feature levels are

[14] A complete disposition of the samples for the survey is provided in Exhibit F. Based on these calculations, the incidence rate for the survey was 17.4 percent, the initial response rate was 15.6 percent, the completion rate for the conjoint task was 94.9 percent, and the net response rate was 14.8 percent.

indicated below. Recall that these features and levels were chosen to be realistic based on both the qualitative interviews and the pretest interviews.

- Pack type. The levels were soft pack and hard pack.[15]
- Level of perceived health risks. The survey emphasized that consumers were to use their personal beliefs about health risks in the choice exercise.[16] The levels were "Health risks are greater than regular cigarettes," "Health risks are the same as regular cigarettes," "Health risks are the same as "light" cigarettes," "Health risks are the same as "ultra-light" cigarettes," and "Health risks are less than "ultra-light" cigarettes."
- Taste. The levels were "Tastes like a regular cigarette," "Tastes like your brand of "light" cigarette," and "Tastes like an "ultra-light" cigarette." Respondents were asked to use their own beliefs about taste, and to assume the taste for a cigarette option was the same as the taste provided by their brand for that cigarette option (to the degree possible).[17]
- Price per pack. The levels were "50% less than what you pay now", "20% less than what you pay now", "The same price that you pay now", "20% more than what you pay now" and "50% more than what you pay now" per pack.[18]

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[15] Qualitative interviews and pretests suggested that the inclusion of a feature such as pack type enhanced the realism of the survey.

[16] The survey uses two-sided introductory statements to emphasize that the respondent is to consider their personal beliefs. Through qualitative interviews and pretests, I found that these descriptions were well-understood by respondents and that they understood they were to use their perceived beliefs about health risks.

[17] Not all brands of "light" cigarettes offer regular and ultra-light versions. Thus, I did not use the words "your brand of" for regular and ultra-"light" cigarettes. Rather, I used a paragraph description in which the survey told the respondent that, if the respondent's brand of "light" cigarette offers a regular (ultra-light) version, then the respondent should consider taste like that version. Otherwise, I listed examples of popular cigarettes. Through qualitative interviews and pretests, I found that these descriptions were well-understood by respondents.

[18] To aid respondents the survey provided examples of how to convert percentage reductions (increases) to dollar amounts. Through qualitative interviews and pretest, I found that these descriptions and calculations were clear and well-understood by respondents.

31. For each respondent, their choices from the choice sets they were shown were used to estimate with hierarchical Bayes (HB) the vector of partworths for each respondent.[19] The options in the choice sets were chosen randomly to assure equal expected values of each feature and level. The designs were highly efficient.[20] Intuitively, in our study, an efficient design provides the estimates of partworths with high precision. Efficiency refers only to precision.

32. Following these sixteen choice sets, respondents were thanked and the interview was concluded.

IX. Analysis

33. Hierarchical Bayes estimates for the partworths for each respondent were obtained from the data with software developed by Sawtooth Software, Inc.[21] The software uses a Bayesian procedure to update (estimate) the relative values of the partworths for each respondent. These heterogeneous partworths are used in the simulation model. In Exhibit G, I summarize the (average) partworths where the average is computed over all respondents within a group.[22] Exhibit G also shows the standard deviation of the estimated partworths (across respondents), which demonstrates the heterogeneity in respondents. (The higher the standard deviation, the more the partworths vary over respondents. It is natural that partworths vary

[19] Technically, this is a Bayesian procedure in which we are obtaining the best update of the partworths based on the data. This means that we represent all of the information about the partworths, including the mean (average) for each respondent and a measure of the uncertainty about the partworths. For brevity I refer to these complicated descriptions as simply the estimates of the partworths.
[20] For more technical descriptions see Sawtooth Software Technical Paper, "Choice-based Conjoint (CBC) Technical Paper," 2001. Efficiencies were 100% for the complete-enumeration randomized designs.
[21] Sawtooth Software CBC/HB Module for Hierarchical Bayes Estimation, Version 3.1.
[22] In conjoint analysis we are dealing with choices among alternative products. Thus, partworths indicate the value to a respondent in changing one level of a feature for another. For example, our analyses measure the value of having a soft pack relative to having a hard pack. For example, based on the averages in Exhibit G this relative value is 12.7, that is, 6.35 – (-6.35) = 12.7. Because the relative values are used in the forecasting model, we report the mean partworths such that they sum to 0.00 across feature levels within a feature. For example, 6.35 + (-6.35) = 0.00.

among respondents. This indicates that different respondents may value the various features differently. As described in subsequent paragraphs of this report, I take into consideration this heterogeneity in my analyses.) When interpreting Exhibit G it is also useful to keep in mind that the partworths do not vary independently across respondents. Technically, there are also covariances (across respondents) among the various partworths. For example, respondents who place a higher importance on perceived health risks also place a lower importance on taste as indicated by a -0.22 correlation between the full-range importances of these features.

34. The average values of the estimated partworths in Exhibit G indicate that, on average, "light" cigarette consumers value lowering their health risks. That is, the average of the partworth for having lower health risks than an "ultra-light" cigarette is statistically significantly larger than the average partworth for having health risks greater than a regular cigarette.[23] This is also true for health risks the same as "light" cigarettes compared to health risks to the same as regular cigarettes.[24] The values of the partworths for health risks do not vary significantly among users of the major brands of light cigarettes.[25]

35. In order to establish the appropriateness of using the estimated partworths to forecast consumer behavior, I test the fit and predictive ability of the conjoint analysis estimates. An appropriate statistic with which to evaluate the model is the percentage of uncertainty that is explained by the model.[26] This statistic is known as "U^2." U^2 is a ratio of the "information explained by the probabilistic model" divided by "the total uncertainty (entropy) of the system." Perfect predictions would have a U^2 of 1.0. A "null" model, which predicts that each

[23] t-statistic = 33.9 and $p \leq 0.00$
[24] t-statistic = 31.9 and $p \leq 0.00$
[25] F-statistic = 1.094, p = .222, using Wilk's Lambda method.
[26] Hauser, John R. (1978). "Testing the Accuracy, Usefulness, and Significance of Probabilistic Choice Models: An Information-Theoretic Approach, *Operations Research*, Vol.26, No. 3 (May-June), 406 – 421.

respondent would choose randomly among the four profiles in each choice set (predicted probability = 0.25 for every profile), would have a U^2 of 0.0. I examine U^2 for the choice tasks that were used to estimate the model and for holdout choice tasks (choice tasks that were "held out" of the estimation in order to test predictive ability).

36. To get a valid indicator of holdout performance, I used the HB method excluding one choice task for each respondent from the estimation. I repeated this process three times using a different choice task each time. The resulting statistics are the average of the three separate validation calculations. If U^2 for the estimation profiles is at a reasonable level, then it is appropriate to conclude that the HB estimates explain a reasonable level of consumer behavior and that the features as specified capture much of consumer preferences. (U^2 measures the ability of the model to explain consumer choices. The partworths and the forecasts are still the best estimates given the data.) To establish "reasonable" I compare the HB estimates to those obtained by a multinomial logit model in which the partworths are the same for every respondent (homogeneous multinomial logit or "HML"). I also examine whether or not the HB estimates "over-fit" the data. "Over-fitting" would occur if the estimates from the estimation partworths could not predict the choices in the holdout data to a reasonable level of precision.

37. For the HB estimates obtained from estimation on 15 of the 16 choice tasks, the average estimation U^2 is 0.522.[27] The average U^2 for the holdout task is 0.459. For the model in which the partworths are the same for every respondent (HML), the estimation U^2 is 0.288

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[27] In calculating U^2 for the estimation sample it is appropriate to adjust for the degrees of freedom in the model. This is appropriately conservative because it lowers the U^2 value. In an HB model we need to estimate the degrees of freedom as affected by the hierarchical constraints. This is a technical calculation involving the Deviation Information Criterion (DIC). We adjust the degrees of freedom by lowering the likelihood value by the degrees of freedom and then computing a ρ^2 fit statistic. See Bruce G. Hardie, Eric J. Johnson, and Peter S. Fader (1993), "Modeling Loss Aversion and Reference Dependence Effects on Brand Choice," *Marketing Science*, 12, 4, (Fall), 389. Because Hauser (1978) demonstrates that ρ^2 is numerically equal to U^2 this correction for degrees of freedom can also be used for U^2 while retaining the intuitive interpretation of U^2.

and the holdout U^2 is 0.279. Thus, the HB estimates are substantially better than the HML estimates. This is true for both the estimation data and the holdout data. Furthermore, there is only a modest drop off in predictive ability for the holdout data suggesting that the HB estimates are not over-fitting the data. Finally, the HB-based U^2 value for the holdout task is substantially above the HML-based U^2 value and substantially above that which would be obtained from random choice. Based on these statistics, it is my opinion that the HB estimates are appropriate for making predictions with respect to alternative scenarios.

38. Because U^2 is a technical statistic, it is informative to look at a more intuitive measure, that is, the percentage of choices that can be predicted correctly with the HB estimates. For this statistic, the "null" model of random choice would predict the choice correctly only 25 percent of the time (one time out of four). In this case, the estimated partworths correctly predict the chosen alternative 87.6 percent of the time for the estimation data and 72.3 percent of the time for the holdout data.[28] By contrast, the homogeneous multinomial logit (HML) analysis correctly predicts the choice only 59.5 percent of the time for the estimation data and 60.7 percent of the time for the holdout data. For both the estimated data and for the holdout data, the HB estimates are significantly better at predicting choice than are the HML estimates at the 0.00 level. Furthermore, both the HB and the HML estimates are significantly better at predicting choice than the null model at the 0.00 level.[29]

39. The statistical tests based on the statistic of "percentage of choices correctly predicted" lead

[28] Unlike the more rigorous U^2 statistic, there is no easy way to adjust the first-choice prediction percentage for degrees of freedom. Thus, we consider the more conservative holdout percentage of 72.3%.

[29] When comparing HB and HML, t-statistic = 96.0 for fit and 8.70 for holdout; when comparing HB and the null model, t-statistic = 192.4 for fit and 32.9 for holdout; when comparing HML and the null model, t-statistic = 87.4 for fit and 23.24 for holdout. (The null model is a vector of hits with a 25 percent hit rate.) For all of these t-statistics, $p \leq 0.00$. Data for the fit t-tests were based on 627 respondents x 15 choice tasks x 3 different holdout tasks (Choice tasks 4, 8, or 16) = 28,215 observations. The hits data, a series of ones and zeros, were formed into 28,215 x 1 column vectors for HB and HML. For the holdout cells, there were 627 respondents x 1 choice task x 3 different holdout tasks = 1881 observations. Paired t-tests were performed on the resulting vectors for HB vs. HML.

to the same conclusions as the more formal U^2 tests. It is my opinion that the HB estimates are appropriate for making predictions with respect to alternative scenarios.

40. In an HB CBC analysis of consumers, I estimate the partworths that describe the process by which consumers choose among alternative cigarette options. Technically, this is an additive model because we sum the partworths of the feature levels in order to estimate the utility of an option.[30] An additive model is a general representation. The partworths can represent both "compensatory" and "non-compensatory" decision rules. In a compensatory decision rule, improvements in some features can compensate for decreases in other features. For example, in a compensatory rule, we might find that better taste, better health risks, and lower price might compensate for a less-preferred pack type. In a non-compensatory rule, improvements in some features will not compensate for a lowered level of a more important feature. A common type of non-compensatory rule is a lexicographic rule in which a consumer first chooses based on one feature, say pack type, then another, say taste, then another, etc. until only one option remains. A lexicographic rule is similar to alphabetical order. The word "azygous" comes before "babble" in the dictionary because "a" is before "b" in alphabetical order. The "a" and two additional "b's" in babble do not compensate even though azygous has a "z," a "y," and a "u." Technically, an additive model represents a compensatory rule when the relative partworth values are not too extreme. An additive model can represent a lexicographic rule when the partworths are extreme. I address what I mean by "extreme" in subsequent paragraphs.

41. Because an additive model represents both compensatory and non-compensatory rules, the CBC analyses in this report are appropriate whether or not respondents are compensatory. However, I can use the estimated partworths to examine whether or not improvements to

[30] I also tested a model with full interactions. The additive model is a better description of consumers for these data.

some features of cigarettes can compensate for less-preferred levels of other features. The use of compensatory, non-compensatory, and lexicographic rules is an empirical question that depends on the product category. For example, in a recently completed study, I found that for the choice of SmartPhones, many respondents use lexicographic rules such as rejecting an extremely high price.[31]

42. If a consumer is using a lexicographic rule, then no improvements in lesser important features can compensate for any improvement in the most important feature. Suppose that pack type is the most important feature and suppose the consumer prefers a hard pack. Then the consumer is lexicographic with respect to pack type if the importance of pack type (the partworth of a hard pack minus the partworth of a soft pack) is greater than the sum of the importances of taste, health risks, and price. For features with multiple levels, the formulae are complicated but can be computed.[32]

43. Using the partworths estimated by HB CBC, I examined whether consumers are lexicographic with respect to pack size, taste, health risks, or price. I first identified the most important feature for each respondent and then compared the partworth difference for any change in that feature to the sum of the importances for the other features. By this test, 622 of the 627 respondents were not lexicographic (99.2%). The remaining five respondents exhibited lexicography with respect to pack type.[33] No one was lexicographic (at the top level) with respect to taste, health risks, or price. In other words, for 99.2 percent of the respondents and for the features of taste, health risks, and price, improvements in some

[31] Yee, Michael, John Hauser, James Orlin, and Ely Dahan (July 2005), "Greedoid-Based Non-compensatory Two-Stage Consideration-then-Choice Inference," under review, *Marketing Science*.

[32] For detailed formulae see Yee, et. al. (ibid) and Jedidi, Kamel and Rajeev Kohli (2004), "Probabilistic Subset-Conjunctive Models for Heterogeneous Consumers," Working Paper, Graduate School of Business, Columbia University (November).

[33] For these five respondents, after choosing their favorite pack type lexicographically, the remaining three features were evaluated with a compensatory decision rule.

features can compensate for decreases in other features.

44. Using the HB partworths, I can draw conclusions about whether perceived health risks are a significant contributing factor in "light" cigarette consumers' purchase decisions.[34] I begin by examining the importances that consumers place on health risks. In the HB CBC analysis, the importance of health risks is the difference between the partworth for "Health risks are less than an "ultra-light" cigarette" and "Health risks are greater than a regular cigarette." For 90.1 percent of the 627 respondents, this difference was positive, indicating that, given the choices made by respondents who answered the survey, the best estimate of their importance for health risks is positive. I study this more closely by examining statistical significance. In particular, for some of the remaining 9.9% of the respondents the choices might be such that we cannot be statistically confident that the importance they place on health risks is different than zero. Because we are testing whether the importance is positive (or, in other tests, negative), the appropriate statistical test is a one-tailed statistical test.

45. The HB analysis provides both means and standard deviations of the partworths for every respondent. I use these means and standard deviations to perform the appropriate one-tail t-tests (statistical test) for each respondent in the sample. For 76.4 percent of the respondents, the importance of health risks is positive and statistically significant at the 0.10 level and for 69.7 percent of the respondents the importance of health risks is positive and statistically significant at the 0.05 level. For only 2.1 percent of respondents the importance of health

[34] When doing so, it is important to distinguish between the legal term "significant" and the statistical term "significant." Because I am not a lawyer, I provide no legal opinion with respect to the legal term "significant." I provide expert opinions about percentages. When I use the term "significant" in a statistical sense, I refer to the probability that the observed outcome could be due to chance alone. It is common in scientific studies to set minimum level of significant level of 0.05, which means that there is a 5 percent chance or less that the observed data are due to chance. (Some scientists may also require a 0.01 level and others may report results at the 0.10 level with the appropriate caveats. Many of the statistical significance levels in this report are significant at better than the 0.01 level as indicated.) When I use the term "significant" in a non-statistical sense I am relying on counsel to provide a legal interpretation.

risks is negative and statistically significant at the 0.10 level and for 1.1 percent of the respondents the importance of health risks is negative and significantly negative at the 0.05 level. For the remaining respondents (29.2 percent at the 0.05 level, 21.5 percent at the 0.10 level), at the level of the individual respondent, the data are not sufficient to classify respondents at a high level of statistical significance. In summary, at the 0.05 level, I am statistically confident that about 1 percent of the respondents do not place a significant positive value on health risks. For almost 70 percent of the respondents I am statistically confident that they place a significant positive value on health risks. For the remaining respondents, approximately 20%, my best estimate is that about 2/3rds of the respondents place a positive value on health risks – for a total of 90.1% as summarized in the previous paragraph.

46. I further address whether perceived health risks are a significant contributing factor in "light" cigarette consumers' purchase decisions by ranking importance measures of the feature. (In this paragraph I use the word, "significant" in a non-statistical sense.) I first consider only those respondents for whom I estimate that the respondent places a positive value on health risks. I next compute the importance of each feature as the difference between the maximum partworth for that feature and the minimum partworth for that feature. I then rank these feature importances. Health risks are ranked above price by 26.8 percent of these consumers, above taste by 68.9 percent of the consumers, and above pack type by 94.4 percent of the consumers. Health risks are ranked above price or taste by 76.1 percent of these consumers. Ranking these importances at the respondent level, and then aggregating these ranks, shows that perceived health risks is most important for 18.4 percent of these respondents, second most important for 57.7 percent of these respondents, and third out of four for 21.9 percent of

these respondents. Cumulatively, this shows that health risks is third or better in importance for 98.1 percent of these respondents. Overall, on average, price was most important, health risks second, taste third, and pack type fourth.[35] It is also useful to look at the ranks in the absence of price, since the other attributes represent what the consumer obtains by buying the cigarette in exchange for payment of the price. The relative rankings for the remaining three attributes are unchanged, i.e., health risks is, on average, most important, followed by taste and then pack type.[36] From these analyses, I conclude that perceived health risks is a significant contributing factor in the purchase decisions of 98.1 percent of "light" cigarette consumers who place a positive value on health risks.

X. Calculations of Value of Perceived Reduced Health Risks Associated with "Light" cigarettes

47. The HB partworth estimates can be used to determine the monetary value that consumers place on a having the lower perceived health risks associated with "light" cigarettes. I illustrate how to calculate the monetary value with two methods which indicate (1) how individual consumers value health risks and (2) how the market values health risks. The Willingness-to-Pay (WTP) method uses the relative partworths of price changes compared to the relative partworths of feature changes to impute the amount that each respondent would be willing to pay for lower health risks. I summarize these willingness-to-pay dollar values across respondents. The Market-Based method uses the partworths to predict how respondents would react in a "but-for" world in which I change the price level and the health

[35] The average rank for price is 1.52, for perceived health risks 2.07, for taste 2.62, and for pack type 3.79. Standard errors for each average rank were in the range of 0.02 to 0.04.

[36] The average rank for perceived health risks is 1.37, for taste 1.80, and for pack type 2.83 in the absence of price. Standard errors for each average ranks are in the range of 0.030 to 0.042.

risks level of a "light" cigarette. For each respondent the partworths (and the characteristics of the "but-for" world) imply choice probabilities. These choice probabilities, in turn, imply a market share for each "but-for" cigarette option. I use the Market-Based method to determine the price difference at which the market, as represented by the respondents, would be indifferent between a "light" cigarette with perceived health risks the same as "light" cigarettes and a "light" cigarette with perceived health risks the same as regular cigarettes. I also use the Market-Based method gain insight on the price discount that would be needed to sell a cigarette with perceived health risks greater than regular cigarettes.

48. With the Willingness-to-Pay method, I first calculate the number units of consumer utility that correspond to a one-percent change in price. For example, Exhibit G indicates that, on average, a change in price from the current pack price to 50 percent off is worth 47.9 units of consumer utility. This is equivalent to saying that, on average, 47.9 units of consumer utility correspond to a price drop of 50 percent or that, based on the ratio of these two numbers, each unit of consumer utility corresponds to a price change of 1.04 percent.[37] For these same respondents, the number of units of consumer utility that are lost, on average, for going from perceived health risks the same as "light" cigarettes to perceived health risks the same as regular cigarettes, are 33.5 units of consumer utility. These calculations are illustrative. I perform these calculations for each respondent in the sample and then summarize the results of the respondent-level calculations. To complete the illustration, I consider a hypothetical situation in which all respondents have partworths equal to the average partworths. In this hypothetical case, the willingness-to-pay for a reduction in health risks from that perceived for regular cigarettes to that perceived for "light" cigarettes would be worth 34.8 percent

[37] I choose the range of price discounts to consider to be consistent with the calculated WTP. In this illustrative case, the example price discount of 38.4% is in the range of 20% off to 50% off, thus it is appropriate to compare the partworths for price discounts of 38.5% and 50% off as opposed to using 20% off for the lower end of the range.

(1.04 percent for each unit of consumer utility times 33.5 which represents the number of units of consumer utility gained by reducing the perceived health risk). This calculation for the average partworths is hypothetical and provided in this paragraph to illustrate the calculations that are made for each respondent. When partworths vary by respondent (heterogeneous respondents), the median willingness-to-pay can either increase or decrease relative to this hypothetical situation. When I complete this calculation for each respondent and take the median across respondents, I calculate a median willingness-to-pay of 47.3 percent.[38,39]

49. The Market-Based method uses the HB partworths to simulate a market in which all respondents react to the same price. Such Market-Based simulations are used often by firms to simulate what would happen if a new product were introduced to a market or if an existing product changed its features. It is well known in the market research industry that the forecasts based on such Market-Based simulations are sufficiently accurate that firms routinely make decisions based on these Market-Based simulations. The Market-Based method uses the complete population distribution of partworths (as estimated by HB) for

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[38] I use the median as a statistic of central tendency rather than the mean because (1) willingness-to-pay is the ratio of two estimates, each with its corresponding variance, (2) the Bayesian methods provide complete estimates of the distribution of the partworths for each individual respondent (for the market-based method), (3) the median allows me to avoid extrapolation beyond the ranges of the price levels in the survey, (4) the median is a more robust statistic under these conditions, and (5) the median provides an accurate summary of central tendency. In the analyses in this report the median is appropriately conservative because the WTP that I obtain from the median is less than the WTP that I obtain from the less-robust means. Calculations using other robust estimators yield answers that are similar to those obtained for the median. In addition, I performed sensitivity analyses using slightly different formulae to calculate WTP. For example, when I use formulae that take the non-linearity of the partworths into account, I obtain a median WTP of 45%.

[39] Because the survey allows the respondent to react to price changes up to 50%, any willingness-to-pay calculation that results in an estimate greater than 50% is an extrapolation and should be treated appropriately. In other words, if the extrapolations yield an estimated WTP greater than 50%, then we can be confident that the WTP is greater than 50%, but we cannot be confident in its exact value. For example, extremely high WTP results are due to extrapolation effects. Because the calculated median of 47.4 percent is less than 50 percent, the median is not affected by the details of the extrapolation and is, thus, robust with respect to extrapolation. To calculate this median we need only know that some consumers have WTPs that are above 50 percent. We do not need to calculate the exact values. On the other hand, if we were to use the mean WTP, the calculation of the mean would involve respondents whose estimated WTPs are based on extrapolation. In summary, the median is a robust measure that is, appropriately, conservative.

each respondent. These partworths represent how each respondent will react to changes in features or price. Using the probability model (multinomial logit model) underlying HB I then use these partworths to predict the probabilities that each respondent would choose each of the service bundles from a defined choice set.

50. To calculate the value of a reduction in perceived health risks, I consider an alternative scenario in which there are only two alternative "light" cigarette options: one option with perceived health risks the same as "light" cigarettes and second option with perceived health risks the same as regular cigarettes. For each of these cigarette options I hold all other features constant at the same levels (type of pack, taste like the respondent's brand of "light" cigarette, and, for the first option, price that the respondent pays now for the respondent's brand of "light" cigarette). I then simulate markets in which the second cigarette option is offered at varying percentage changes in prices. This second cigarette option has all of the "light" cigarette features except that the perceived health risks are the same as regular cigarettes. I lowered the price of the second cigarette option until the market was indifferent between the two cigarettes. That is, I find the percentage price reduction for the second cigarette option such that half of the market chooses the first ("light" health risks) "light" cigarette option and half of the market chooses the second (regular cigarette health risks but lower priced) cigarette option. The price discount that is necessary for market indifference is the monetary value that the market places on the difference in perceived health risks.

51. There are two ways in which I calculate market share using the HB partworths. The difference is technical and requires a detailed understanding of CBC and the HB analysis. I attempt to provide a lay explanation here. Recall that HB provides the best estimate of a respondent's partworths. If I take the best estimate for each respondent, I obtain a market

simulation based on the "point" estimate for each respondent of that respondent's partworths. This "point" estimate gives a "point" estimate for each respondent's utility for each profile in the market. The respondent "chooses" the profile with the highest utility. Using this method I find the price at which the market is indifferent. I provide the results of this calculation in Exhibit H as labeled by "First Choice Simulation." The words, "first choice," refer to the fact that I use the best estimate and calculate the respondent's first-choice cigarette option, i.e., which cigarette option has the highest overall utility, based on the sum of the option's partworths for that respondent. The second method uses detailed information (from the HB estimation) on the unobserved features and randomness in consumer choice. In accord with the logit model, utility is based on the best estimate of the partworths plus a random error consistent with the estimation. I repeatedly sampled from the distribution of this error and compute the respondent's first choice cigarette option (based on appropriate probabilities) for each sample that is drawn. This is known as the "Randomized First Choice Simulation." By using two procedures to obtain a market-indifference price, I am able to determine whether or not the two procedures provide similar estimates for the data obtained from the survey described in this report. The variation in the two procedures provides insight on the possible range of estimates.

52. The results of the Market-Based simulations are given in Exhibit H. The Market-Based method estimates that the value of the change in perceived health risks from the same as regular cigarettes to the same as "light" cigarettes is approximately 47.1 percent of the price per pack by the first-choice method and 39.8 percent of the price per pack by the randomized first-choice method. Thus, using the Market-Based method I estimate that the value of the change in perceived health risks from the same as regular cigarettes to the same as "light"

cigarettes is in the range of 39.8 to 47.1 percent of the price per pack. Because these estimates are approximately equal to those obtained by the Willingness-to-Pay method (47.3 percent), it confirms my confidence that the estimated range is accurate.

53. The lowest level of price used in the Choice-Based Conjoint analysis was "50% LESS than what you pay now" and the highest level of price was "50% MORE than what you pay now." Thus, the data can be used confidently to calculate any willingness-to-pay that is between 50 percent less and 50 percent more than what the consumer now pays. If the willingness-to-pay calculation results in a number that is larger than 50 percent more (or less than 50 percent less), then we can be confident that the willingness to pay is larger than 50 percent more (or less than 50 percent less). However, because the calculation is based on extrapolation, we should be extremely cautious when interpreting the exact value. I, therefore, use methods of analysis that avoid extrapolation. In particular, I calculate that more than 75 percent of the consumers would be willing to pay more than 50 percent of the price per pack of their cigarettes to decrease health risks from greater than regular cigarettes to health risks the same as "light" cigarettes.[40]

54. The data and analyses in this report can also be used confidently in a Market-Based Simulation to examine markets in which a cigarette is priced at 50 percent less that what the consumer now pays. I consider a scenario in which there are only two alternative "light" cigarette options: one option with a perceived health risks the same as "light" cigarettes at a price that the respondent pays now for the respondent's brand of "light" cigarette and second option with perceived health risks greater than regular cigarettes but with a price that is 50 percent less than the respondent pays now for the respondent's brand of "light" cigarette. For each of these cigarette options I hold the other features constant at the same levels (type of

[40] The estimates are 75.4% and 75.3% for simple and non-linear price response calculations, respectively.

pack and taste like the respondent's brand of "light" cigarette). Using the First Choice Simulation, I estimate that the cigarette with health risks the same as "light" cigarettes would obtain a 75.4 percent market share even though the second higher-health-risks cigarette was offered at a price 50 percent less than the respondent pays now. Using the Randomized First Choice Simulation, I estimate the market share of the cigarette with health risks the same as "light" cigarettes to be 72.3 percent. Thus, in order for the market to be indifferent between the two types of cigarettes, the cigarette with health risks greater than regular cigarettes would have to offer substantially more than a 50 percent discount per pack.

XI. Summary of Conclusions

55. The scientific methodology used to design, execute, and analyze the study in this report is sound, reliable, and valid. The results can be relied upon to draw inferences about whether health risks are a significant contributing factor in consumer decisions to smoke "light" cigarettes and what proportion of "light" cigarette-smoking consumers relied on health risks as a significant contributing factor. The results can also be relied upon to draw inferences about the value to consumers of the change in perceived health risks from the same as regular cigarettes to the same as "light" cigarettes. I illustrate how the results can be used with methodologies based on (1) consumers' willingness-to-pay for reduced health risks and (2) the market's valuation.

56. Based upon an examination of the partworths for perceived health risks, I find, to a reasonable degree of scientific certainty, that 69.7 percent of "light" cigarette consumers place a statistically significant positive value on perceived health risks, and only 1.1 percent place a statistically significant negative value on perceived health risks. In accordance with these assessments and measurements, 90.1 percent of "light" cigarette consumers place a

positive value on this change in perceived health risks.

57. Based upon an examination of feature importance, I find, to a reasonable degree of scientific certainty, that perceived health risks are a significant contributing factor in the cigarette purchase decisions of 98.1 percent of "light" cigarette consumers who place a positive value on perceived health risks.

58. Based on the Willingness-to-Pay method, I estimate that the median value of the change in perceived health risks from the same as regular cigarettes to the same as "light" cigarette is 47.3 percent of the price per pack.

59. Based on the Market-Based method, I estimate that the market value of the change in perceived health risks from the same as regular cigarettes to the same as "light" cigarette is between 39.8 percent and 47.1 percent of the price per pack.

60. Based on the Willingness-to-Pay method, I estimate that more than 75 percent of the consumers would be willing to pay more than 50 percent of the price per pack to decrease health risks from greater than regular cigarettes to health risks the same as "light" cigarettes.

61. Based on the Market-Based method, I estimate that the market value of the change in perceived health risks from greater than regular cigarettes to the same as "light" cigarettes is substantially more than 50 percent of the price per pack.

62. Based on the methodologies described in this report, derived from both consumer Willingness-to-Pay and Market-Based simulations, I conclude, on the basis of the best available information and methodologies, that individual consumers and the market value of the change in perceived health risks from that of a regular cigarette to that of a "light" cigarette is between 39.8 percent and 47.3 percent of the price per pack.

63. Based on the above analysis of the partworths, at most 8/10$^{\text{ths}}$ of 1 percent of the respondents

use a non-compensatory lexicographic decision rule for taste, health risks, pack type, and price. For all other respondents and for the features of taste, health risks, and price, high values on some features can compensate for low values on other features.

Dr. John R. Hauser

Date

12-19-05